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Abstract

As the Earth warms, the spatial and temporal response of seasonal snow remains uncertain. The global snow science community estimates snow cover and mass with information from land surface models, numerical weather prediction, satellite observations, surface measurements, and combinations thereof. Accurate estimation of snow at the spatial and temporal scales over which snow varies has historically been challenged by the complexity of land cover and terrain and the large global extent of snow-covered regions. Like many Earth Science disciplines, snow science is in an era of rapid advances as remote sensing products and models continue to gain granularity and physical fidelity. Despite clear progress, the snow science community continues to face challenges related to the accuracy of seasonal snow estimation. Namely, advances in snow modeling remain limited by uncertainties in modeling parameterization schemes and input forcings, and advances in remote sensing techniques remain limited by temporal, spatial, and technical constraints on the variables that can be observed. Accurate monitoring and modeling of snow improves our ability to assess Earth system conditions, trends, and future projections while serving highly valued global interests in water supply and weather forecasts. Thus, there is a fundamental need to understand and improve the errors and uncertainties associated with estimates of snow. A potential method to overcome model and observational shortcomings is data assimilation, which leverages the information content in both observations and models while minimizing their limitations due to uncertainty. This article proposes data assimilation as a way to reduce uncertainties in the characterization of seasonal snow changes and reviews current modeling, remote sensing, and data assimilation techniques applied to the estimation of seasonal snow. Finally, remaining challenges for seasonal snow estimation are discussed.

1. Introduction and Motivations

For many regions of the world, seasonal snow acts as a “virtual” reservoir that accumulates in the winter and melts in spring, storing and subsequently providing water for urban and agricultural users (Viriroli et al., 2007). About 15% of the world's population derives the majority of its water supply from seasonal snowpack (Barnett et al., 2005). Snow also presents hazards such as flood and avalanche risks, disruption to transportation, and impacts on livestock, wildlife, and infrastructure (Musselman et al., 2018; Berghuijs et al., 2016; Nadim et al., 2006; Rooney et al., 1967; Tachiiri et al., 2008; Descamps et al., 2017; Croce et al., 2018). In addition, snow-cover strongly influences weather and climate. The highly reflective, emissive, and insulative properties of snow compared to other surfaces alter the heat and moisture fluxes between the land and the atmosphere (Gong et al. 2004, Trujillo et al., 2012). The feedback effects of snow on atmospheric circulation and downstream weather patterns can have inter-continental impacts. For example, anomalous snow cover conditions in Siberia strongly influence North American weather (Cohen and Entekhabi, 2001; Dutra et al., 2011; Henderson et al., 2018) and spring snow cover in the Himalaya can affect the formation of the Indian monsoon (Senan et al., 2016; Xu & Dirmeyer 2011, 2013). Accurate representation of snow cover in models can improve the skill of numerical weather prediction and water resource management. Snow estimation is “a trillion-dollar science question” (Sturm et al., 2017) that is increasingly important as global warming forces substantial change.

Declines in snow-covered area and volume, and shifts to earlier snow disappearance, have been observed across the Northern Hemisphere since many satellite records began (Déry and Brown, 2007; Foster et al., 1996; Hammond et al., 2018; Brown et al., 2017; Notarnicola, 2020). To date, snow loss attributed to warming temperatures has primarily occurred in spring and at the geographic margins of historical seasonal snow cover, namely at mid-latitudes and lower elevations (Pierce et al., 2008; Hammond et al., 2018; Mote et al., 2018). Snow cover reductions in response to warming impact the Earth system via complex feedbacks that are best addressed using models. For example, while warming is accelerating the global hydrologic cycle (Huntington et al., 2006), snowmelt rates may be slower in a warmer world due to less snow persisting into the warmest months (Musselman et al., 2017). Similarly, Arctic warming will degrade permafrost (Lawrence et al., 2008), yet shallower snow provides less insulation of soils from winter air temperatures, resulting in colder soils in a warmer world (Groffman et al., 2001). Accurate monitoring and modeling of snow improves inclusion of these process interactions in future Earth system projections while also serving highly valued global interests in water supply, weather forecasts, and agriculture (Sturm et al., 2017).

While spring snow cover reductions are evident in satellite records (Bormann et al., 2018), station observations (Mote et al., 2018; Klein et al., 2016), and global model reanalysis (Rupp et al., 2013; Wu et al., 2018), there remains much variability and uncertainty in the spatial and seasonal patterns. For example, increasing autumn snow cover trends in the Northern Hemisphere, especially at Eurasian high latitudes, have been attributed to seasonal precipitation increases (e.g., Allchin and Dery 2017, Hori et al., 2017). Several studies have questioned this positive trend, arguing that it is inconsistent with North American autumn surface temperature warming trends (e.g. Brown and Derksen, 2013; Hori et al., 2017). Similarly, while there is a general consensus that snow volume and mass over the terrestrial Arctic is decreasing, the literature has reported highly variable regional trends (Brown et al., 2017). The limited unanimity on how global snow patterns have changed is likely due the lack of comprehensive and accurate snow estimates from models and/or remote sensing observations. There is a critical need to improve snow estimates in reanalysis products, operational models, and future climate projections.

Modeling and remote sensing approaches have inherent uncertainties and limitations (Frei et al., 2012). Uncertainties in models are mainly associated with their physics and parameterization schemes or error-prone input forcings such as precipitation, temperature, and windspeed (Musselman et al., 2015; Raleigh et al., 2016). Model errors can be reduced with careful configuration. For example, when run at sufficiently high grid spacing, a properly parameterized regional climate model can resolve orographic precipitation fields better than observation networks (Lundquist et al., 2019). Similarly, remote sensing techniques have inherent limitations due to temporal, spatial, and technical constraints on critical snow variables. Careful assessment and model process representation is required to represent global snow patterns and to disentangle the relative contributions of internal climate variability and anthropogenic forcing.

Simulating and observing fine-scale spatial and temporal seasonal snow-cover patterns has historically been challenged by a high degree of environmental complexity and limited *in situ* observations (Peters-Lidard et al., 2019). Important advances by the snow science community allow us to better understand the role and interactions of snow in Earth systems. These advances are possible as remote sensing products and models continue to increase in granularity and physical fidelity (Clark et al., 2017). Nonetheless, there remain fundamental knowledge gaps. A critical area is the need to document and narrow the uncertainties in snow estimates (Brown et al., 2017) from observations and modeling.

A promising method to alleviate shortcomings in snow models and observations and to improve our ability to monitor changes in seasonal snow is data assimilation (e.g., Houser et al., 1998; Sun et al., 2004; Andreadis and Lettenmier 2006; Girotto et al., 2014ab). Data assimilation combines existing and emerging observations (both *in-situ* and satellite observations) with model estimates, thus bridging scale and limitation gaps between observations and models. Data assimilation can integrate measurements from multiple sensors to improve model estimates of snow properties including mass, commonly referred to as snow water equivalent (SWE). Thus, data assimilation offers the potential to document and reduce uncertainties in snow representation. We argue that only through the assimilation of ground observations and model data can satellite-derived snow depth and SWE fields reach the accuracy level required by the current user community including climatologists, hydrologists, and weather and climate forecasters (Tedesco 2012).

The purpose of this article is to review current techniques used to estimate seasonal snow and to elucidate outstanding challenges that could be addressed by combining model estimates with remotely sensed observations. The first two sections report the key benefits and limitations of remote sensing and modeling of seasonal snow. The third section presents the concept of data assimilation. Finally, section four provides a brief summary and conclusions of the current techniques for estimating seasonal snow.

2. Snow Modelling

A half-century of thorough inquiry has established numerical representations of the effects of wind (e.g. Schmidt, 1982), topography (e.g. Meiman, 1968), and vegetation (e.g. Golding and Swanson, 1978) on snow distribution. However, the complex relationships between these variables and their high variability in time and space and at different scales continue to challenge snow model predictive skill (Jost et al., 2007). Despite these challenges, the need for accurate predictions of snow water resources has prompted the development of operational numerical snow models for a range of applications including hydrological forecasting (e.g. Anderson, 1985), weather prediction (e.g. Niu et al., 2011), avalanche forecasting (e.g. Lehning et al., 1999), climate modeling (e.g. Bonan, 1998), and retrieval of snow characteristics by remote sensing (e.g. Mätzler and Wiesmann, 1999). Snow models differ in their degree of process representation depending on the intended application (Tarboton et al., 2001; Essery and Etchevers, 2004). In this regard, snow models fall into two general categories: temperature index models and energy balance models.

Temperature index models use empirical relationships between local air temperature and snowmelt to estimate snow depletion (Ohmura, 2001). Although limited in their representations of physical processes, such models have often been used in hydrological forecasting and climate impacts studies. Energy balance snow models, on the other hand, are designed to simulate all energy fluxes into and out of a snowpack and are used to predict snowmelt as a result of the computed net internal energy. These process-based models have been shown to yield improved local SWE estimates over temperature index methods (Walter et al., 2005). Even within general snow model categories, models differ in their representation of snowpack stratigraphy and vary from single layer (e.g. Essery et al., 1999; Schlosser et al., 1997), to three-layer (e.g. Sun and Xue, 2001), to detailed multilayer (e.g. Brun et al., 1992; Jordan, 1991) snowpack representations. Detailed knowledge of the internal snowpack structure is critical for radiative transfer applications in remote sensing (Wiesmann and Mätzler, 1999) and avalanche forecasts (Lehning et al., 1999) and has utility in hydrological and climate change sensitivity applications (Bavay et al., 2009), presumably due to the correlation between snow material structure and surface – atmosphere interactions.

Physically-based snow energy balance models permit the assessment of how snow properties such as density, albedo, emissivity, and conductivity may impact other environmental processes and states. However, their estimates rely on accurate representation of snow physics and input forcings such as precipitation, temperature, and windspeed (Musselman et al., 2015; Raleigh et al., 2016). That is, snow model estimates remain hindered by uncertain forcing (e.g., meteorological conditions) and weaknesses in the snow model, associated with both the fidelity of the equations used to simulate snow processes (structural uncertainty) and the parameter values selected for use in the model equations (Slater et al., 2013). In the case of high uncertainty, simple snow models can be a viable alternative to physically based energy balance models; however, the latter offer more flexibility to benefit from the increasing availability and performance of satellite remote sensing techniques (Section 2) to validate prognostic model states that simpler models may not track (e.g., surface temperature; Hall et al., 2008). The process-based models are often better structured to improve state estimates through data assimilation (Section 3).

Over the past decade, much progress has been made on the evaluation of snow in models, in particular through the Project for Intercomparison of Land-surface Parameterization Schemes (PILPS) (Slater et al 2001) and the Snow Model Intercomparison Project (SnowMIP) (Essery et al. 2009). This progress has recently been extended to snow modules of global land surface schemes in the Earth System Model (ESM) SnowMIP (Krinner et al., 2018). Despite decades of marked model improvements, the comment by Dirmeyer et al., (2006) still holds that "Generally there is mediocre agreement among the models for most of the snow-related variables, suggesting a potential area of continuing weakness in global land surface schemes." Model uncertainty remains a persistent gap in snow estimation. Clear avenues for improvement are: 1) better characterize sources of model uncertainty and 2) improve model structure, forcing data, and algorithms to reduce that uncertainty. The assimilation of remotely sensed and in-situ observations could address these points by characterizing forcing errors (e.g., snowfall precipitation; Liu and Margulis 2019) and by improving model parameterization (e.g., snow albedo; Navari et al., 2018) while tracking and reducing the inherent uncertainty in the system.

3. Remote Sensing of Seasonal Snow

Advances in satellite remote sensing systems continue to revolutionize the way we monitor snow. New generations of sensors and platforms now provide more extensive and global coverage of mountainous regions where seasonal snow accumulates (Schmugge et al., 2002; Frei et al., 2012). To date, however, no satellite mission dedicated to the estimation of snow water equivalent exists. International community efforts such as NASA's SnowEx (Kim et al., 2018) and the Nordic Snow Radar Experiment (Lemmetyinen et al. 2011) aim to better characterize sensor performance and to identify optimum multi-sensor synergies to map critical snowpack properties in future satellite missions.

Due to the nature of interactions between snow cover and electromagnetic radiation of different frequencies, snow can be distinguished from other terrestrial surfaces using satellite observations with various active and passive sensor techniques. Active sensors provide their own source of energy and illumination to the observed objects and the remote sensor detects the return illumination or energy that is backscattered from the target object. Active remote sensing technologies that have been used for estimating seasonal snow include active microwave and light detection and ranging (lidar) techniques. Passive sensors detect the naturally emitted radiation from the Earth surface. The most common passive remote sensing techniques for snow are visible and near-infrared observations (e.g., Cline et al., 1998, Rice et al., 2011, Section 2.1) and passive microwave detection (e.g., Foster et al., 1984; Li et al., 2012, Section 2.2). Furthermore, airborne gamma radiation measurements detect the natural terrestrial gamma radiation emitted from potassium, uranium, and thorium radioisotopes in the upper layer of soil. By measuring the difference in gamma radiation before and after the snow falls, these measurements can be used to estimate snowpack mass (Carroll, 1987; Carrol and Carroll 1989). In general, active sensors offer higher spatial resolutions than passive ones but at the expense of longer repeat times, which can limit the frequency of global coverage.

The spectral properties of snow depend upon several factors including grain size and shape, water content, impurity concentrations, temperature, and depth (e.g., Dietz et al., 2012; Domine et al., 2006; Skiles et al., 2018). Snow remote sensing techniques have primarily focused on estimating three key variables of seasonal snow: 1) snow extent, 2) snow depth and 3) SWE. The snow extent is the surface area that is covered by snow, while depth and SWE provide estimates of snow volume and mass, respectively. Snow extent is generally obtained reliably with high spatial and temporal resolution from visible and near infrared data (e.g., Hall et al., 2002; Painter et al., 2009; Riggs et al., 2017), but sensors retrieving snow depth, such as the Advanced Topographic Laser Altimeter

System (ATLAS) on ICESat-2 (Hagopian et al., 2016) are generally limited in spatial coverage. Comparatively, there is far less confidence in the measurement of SWE (Clifford 2010; Kim et al., 2018).

3.1. Visible Near Infrared Observations

In the visible and near infrared (Vis/NIR) part of the electromagnetic spectrum, snow is highly reflective; satellite sensors measuring in this part of the spectrum can be used to identify the presence or absence of snow. Vis/NIR observations have been used to detect snow cover since the mid-1960s. In particular, Vis/NIR observations can provide regional to global estimates of fractional snow-covered extent or area (Rosenthal and Dozier 1996; Painter et al., 2009; Cortés et al., 2014). Vis/NIR data is often available at spatial resolutions ranging from tens to hundreds of meters with varying temporal resolution (daily to every couple of weeks). These resolutions are generally considered acceptable for the mapping of snow patterns and changes, even in complex mountainous regions (Hammond et al., 2018). **Table 1** reports some of the key Vis/NIR missions targeted to seasonal snow estimation. Examples of Vis/NIR satellite missions are the advanced very high resolution radiometer (AVHRR, Emery et al., 2000), the Landsat suites of satellite (e.g., Dozier 1989) and the moderate resolution imaging spectroradiometer (MODIS, Hall et al., 2002), and more recently, the visible infrared imaging radiometer suite (VIIRS, Riggs et al., 2016a, b) and Sentinel-2 (Gascoin et al., 2019).

One major challenge in snow mapping using Vis/NIR is the discrimination between clouds and snow because of their similar behavior in the visible part of the spectrum (e.g., Miller et al., 2005; Hall et al., 2019). If cloud coverage exceeds certain threshold percentages, a satellite scene can become useless for snow detection. Furthermore, snow grain size (Hall and Martinec 1985; Rango 1996; Foster et al., 1999), impurities (Aoki et al., 2007; Painter et al., 2012; Skiles and Painter 2019), and snow temperature influence the spectral behavior of different snow and ice surfaces in the Vis/NIR spectrum. Finally, snow cover extent does not provide a direct estimate of SWE. Indirect methods, such as retrospective (or reconstruction) techniques (e.g., Molotch et al., 2004; Molotch and Margulis, 2008; Rice et al., 2011; Jepsen et al., 2012; Raleigh and Lundquist, 2012; Girotto et al., 2014a) or data assimilation methods (Section 3) must be used to estimate SWE.

3.2. Lidar Observations

Lidar is an active ranging system that provides high-resolution, high-accuracy surface elevation maps. The emitted laser pulse is reflected off multiple surface features back to the platform and the distance travelled is estimated and used to map surface height. Snow depth can be obtained from two co-registered lidar images – one each for snow-free and snow-covered dates – by differencing the snow surface and bare-ground elevations (Deems et al., 2013). Airborne rather than spaceborne lidar systems (Painter et al., 2016; Deems et al., 2013) are likely the most accurate to date, but are limited to targeted areas on the order of hundreds of km and favorable weather conditions. Major limitations of lidar techniques are that 1) they observe snow depth and not SWE, thus assumptions or complementary in-situ observations must be made about snow density (Smyth et al., 2019); and 2) they are available only at specific locations and for specific times, typically infrequently and often just once per season near peak SWE (Margulis et al., 2019).

3.3. Passive Microwave Observations

The microwave radiation emitted by the Earth surface is attenuated by the snow mass on the ground. For this reason, microwave measurements are more sensitive to the mass of snow than Vis/NIR observations. Another advantage of passive microwave sensors with respect to the Vis/NIR is that they can detect snow at night and in the presence of clouds. Retrieval algorithms have been developed to estimate the snow depth from satellite-based microwave sensors. The retrievals are derived as a combination of microwave brightness temperature differences sensed at different frequencies, weighted by coefficients derived from the difference between vertical and horizontal polarizations. Examples of satellite-based missions that have been widely used to estimate SWE are listed in **Table 1**. These are the Scanning Multichannel Microwave Radiometer (SMMR, e.g., Chang et al., 1987), the Special Sensor Microwave/Image (SSM/I, e.g., Tedesco et al., 2004) and the Advanced Microwave Scanning Radiometer (AMSR-E and AMSR2, e.g., Kelly 2009).

There are a number of limitations to using passive microwave sensors to monitor seasonal snow. For example, the presence of liquid water in the snowpack (Frei et al., 2012; Kelly 2009) and/or vegetation alters the radiation emitted by the surface (Derksen, 2008). Another major shortcoming is the spatial resolution of passive microwave measurements, which is on the order of tens of kilometers (i.e. much coarser than Vis/NIR). At these coarse scales, there can be significant sub-grid heterogeneity within a single remote sensing footprint, especially if estimating SWE in complex mountainous terrain. Finally, passive microwaves tend to saturate around 250 mm of SWE (Foster et al., 2005), and thus are of limited use to estimate deep snowpacks typical of Earth's mountain water towers (Derksen et al., 2008; Viviroli et al., 2007).

3.4. Active Microwave Observations

Active microwave sensors have the potential to determine snow depth or SWE from space with higher resolution than passive microwave sensors. Active microwave remote sensing measures the total backscattered power from snow covered terrain. The total power received by the sensor can be expressed as the summation of backscatter from the air-snow boundary, the snow volume and the snow-ground boundary attenuated by a factor depending on the layered snowpack properties and incidence angle (Tedesco et al., 2014). Active microwave observations are not limited by weather or sun illumination conditions. While most active microwave studies have focused on the detection of snowmelt (Nagler et al., 2016), some early studies showed a very limited sensitivity of active microwave sensors to snow mass (Bernier et al., 1999; Shi and Dozier

2000; Kendra et al., 1998; Strozzi and Matzler 1998). Recently, a few studies have demonstrated the possibility of using active microwave data to estimate SWE (Lemmetyinen et al., 2018, Moller et al., 2017). Currently, Sentinel-1 or RADARSAT-2 are among the few Synthetic Aperture Radar (SAR) missions providing high-resolution backscatter measurements (at C-band; 5.4 GHz) with a revisit time of 6 days suitable for seasonal snow monitoring. Lievens et al. (2019) demonstrated the value of including cross-polarized backscatter measurements from C-band SAR to retrieve snow depth in mountainous areas at regional scales. Further, Conde et al., (2019) used the SAR Interferometry technique and Sentinel-1 C-band data to retrieve SWE estimates with sub-centimeter measurement accuracy and a 20 m spatial resolution.

3.5. Gravimetric Observations

Less common ways to observe snow include gravity measurements. Gravity data collected by the Gravity Recovery and Climate Experiment (GRACE) and GRACE Follow-On (GRACE-FO) satellites can be used to estimate changes in the mass of terrestrial water storage caused by snow and other hydrological factors such as soil moisture, groundwater, lakes, and rivers (Tapley et al., 2004). However, the main shortcomings of GRACE estimates are related to the very coarse spatial resolution (~3 degrees) which limits application to larger river basins and continents, and to the fact that it observes the total sum of terrestrial water storage. Data assimilation of GRACE observations into land surface models (Girotto et al., 2016, Girotto et al., 2017, Girotto et al., 2019) can spatially and vertically downscale the coarse resolution GRACE observations while characterizing finer-scale SWE estimates.

4. Snow Data Assimilation

Despite recent rapid advances, current remote sensing technology and techniques do not adequately meet global operational needs to map seasonal SWE. To this end, there is great promise in the combination of remote sensing technologies with modeling and data assimilation methods to produce optimal SWE maps with sufficient global coverage and near real-time estimates. In general terms, data assimilation is a transdisciplinary tool that has been used in fields spanning Earth sciences and extending to medicine (Albers et al., 2017) and socio-economics (Houser et al., 2013). **Figure 1** illustrates the data assimilation concept.

All estimates of a phenomenon or event (e.g., seasonal SWE) obtained either through modeling (Section 2) or observations (Section 3) have inherent uncertainty and errors. Data assimilation is a tool to bridge models and observations in order to obtain optimized estimates of the specific phenomena of interest. Theoretically, the results of a data assimilation framework should be a statistically optimal estimate superior to that from either the model or observations alone. Modeling errors are linked to uncertainties due to parameterization schemes and input forcings (Section 2). Similarly, remote sensing observations are prone to observation errors due to measurement acquisition (e.g., sensor errors) and to representativeness of the observations. The latter encompasses errors due to unresolved scales and processes, observation-operator error, pre-processing or quality-control error, and sampling error of the observation grid (Janjić et al., 2018). A remaining challenge is a better representation of errors in the observation and models used in data assimilation (Lahoz and Schneider 2014). In general, modeling and observation errors are assumed to be Gaussian because of the relative simplicity and ease of implementation of statistical linear estimation under these conditions and because Gaussian probability distributions are fully determined by their mean and covariance (Lahoz and Schneider 2014), but the actual values of the errors and their full distributions are not known. Thus, statistical assumptions must be used. These assumptions range from which parameters, model inputs, or remote sensing observation to consider as uncertain, to the decision of the error magnitudes. Furthermore, modeling and observation errors are often assumed static in both time and space. In reality, errors vary in space and time and a fully space and time distributed error covariance should be considered (Evensen 2009).

Despite these remaining challenges, data assimilation has been used to improve modeled estimates of snow states, snow physics, model parameters, and sources of uncertainty (Helmert et al., 2018). There exists a wide variety of data assimilation techniques spanning degrees of complexity and the way in which modeling and observation errors are treated. They vary from the simple direct insertion of observations into the model (e.g., Rodell and Houser 2004; Li et al., 2019), where observation are treated as perfect (i.e., zero observation errors), to more mathematical Bayesian methods such as ensemble Kalman filter and particle filter approaches which are designed to account for the uncertainties of the model and observations using error statistics and an ensemble of possible model realizations. While modeling and observation errors are assumed to be of Gaussian shape in the ensemble Kalman filters, particle filters relax this assumption. The following sections expand on applications of data assimilation in the snow science community and cover studies across different spatial scales: from watershed, to regional and global studies.

4.1. Direct Insertion

A simple direct insertion application is provided by Li et al., (2019). They directly insert a blended satellite- and model-based SWE product (Margulis et al., 2016) for the initialization of a seasonal streamflow forecast model applied over the snow-dominated Sierra Nevada. They demonstrate that a direct insertion of the blended SWE product improves the efficiency of the streamflow model predictions compared to the traditional approach where the model simulates seasonal SWE accumulation and melt using gridded meteorological data. In another example, Rodell and Houser (2004) and Toure et al., (2018) directly inserted MODIS snow cover extent in a global land surface model. They improved SWE model estimates using a rule that specifies whether to update the model with the measurements based on the difference between modeled and observed (from MODIS) snow cover extent. While important model improvements can be obtained with a direct insertion approach, the implicit assumption of the technique is that errors and uncertainties in the system are either acceptable or acceptably mitigated with rule-based insertion decisions.

4.2. Ensemble Kalman Filter

The data assimilation approach most commonly used by the snow science community is the Ensemble Kalman Filter (EnKF) in which error statistics are determined from an ensemble of possible model realizations. The literature is rich with articles that use EnKF techniques (and variations) to assimilate SWE observations (either from in-situ or satellite remote sensing) or microwave radiance observations to directly adjust modeled SWE. Radiance assimilation is more effective because it overcomes difficulties arising from the non-unique and complex relationship linking the passive microwave signal to several snow properties (e.g., density, grain size/microstructure parameters, temperature and wetness) (Helmert et al., 2018). This review reports only a few works on assimilating SWE or radiance observations. For example, Slater and Clark (2006) used an ensemble square-root Kalman filter (EnSRF, an approach similar to an EnKF) to assimilate in-situ SWE data into a snow hydrologic model. They report improvements in the simulated SWE during both accumulation and melt periods. In the same year, Durand and Margulis (2006) developed a point-scale radiometric data assimilation experiment where they used synthetic passive microwave observations and concluded that the EnKF was able to recover the true snowpack states. Similarly, Dechant and Moradkhani (2011) examined the ability of an EnKF of remotely sensed microwave radiance data to improve SWE prediction and operational streamflow forecasts. Huang et al., (2017) examined the potential of SWE data assimilation using the EnKF to improve seasonal streamflow predictions in the Pacific Northwest, the Rocky Mountains, and the Sierra Nevada. They found that most EnKF implementation variations resulted in improved streamflow prediction. To conclude, the scientific community agrees that EnKF assimilation of SWE or microwave radiance observations lead to overall improved estimates of seasonal snow and related variables (e.g. streamflow, snow cover, etc.).

The literature contains a few studies where the EnKF has been used to assimilate snow cover extent observations from a wide range of Vis/NIR satellite missions such as Landsat and/or MODIS. Su et al., (2008) investigated the feasibility of an EnKF framework to assimilate satellite observed snow cover extent over North America. The authors concluded that their framework accurately simulated the seasonal variability of SWE and reduced the uncertainties in the ensemble spread. Andreadis and Lettenmaier (2006) and Clark et al. (2006) used the EnKF to assimilate remotely sensed Vis/NIR snow cover observations into a hydrologic model. Their results showed that the EnKF is an effective and operationally feasible solution to update model predictions of snow cover extent. However, the EnKF performance is modest for estimating ephemeral SWE, and limited for deeper snowpacks. As structured, the EnKF leverages the instantaneous correlation between modeled snow cover extent and SWE. This correlation tends to diminish for larger values of SWE, i.e., when changes in SWE do not correspond to changes in snow cover extent (i.e., snow cover extent saturates at 100%). To solve for this weak instantaneous correlation, Durand et al., (2008), Girotto et al. (2014ab), Margulis et al., (2015) and Oaida et al. (2019) presented a smoother version of the EnKF, the Ensemble Kalman Smoother (EnKS). In the EnKS, all snow cover extent observations within an assimilation window are assimilated, thus multiple strengths of the observed snow cover extent signal are leveraged, not only the instantaneous acquisition.

The retrospective or reconstructive use of Vis/NIR satellite observations can provide accurate estimates of SWE. The general idea of such methods builds upon work on deterministic reconstruction techniques (e.g., Molotch et al., 2004; Molotch and Margulis, 2008; Rice et al., 2011; Jepsen et al., 2012) where the maximum (or peak) SWE can be retrieved from a retrospective accumulation of spring-summer potential melt energy fluxes coupled with the disappearance date of snow as ascertained from visible and near infrared images.

4.3. Particle Filter

Other, arguably more sophisticated methods include particle filter (PF) techniques (Arulampalam et al., 2002). Similar to the EnKF, the PF is a sequential Monte Carlo approach, but it does not depend on the assumption of a Gaussian distribution of errors. PF techniques typically require larger ensembles to characterize the full probability distribution of state variables and consequently their uncertainties via resampling sets of state variables. Leisengring and Moradhkani (2011) assimilated SWE in the National Weather Service model while Margulis et al. (2015) derived an ensemble PF approach to estimate SWE from the assimilation of snow cover extent. Both studies compared the PF to the EnKF. Their results suggest that the particle filter is superior to the EnKF-based methods for predicting model states and parameters. Thirel et al. (2013) improved modeled snow cover extent and runoff by assimilating MODIS snow cover products into a distributed hydrological model using a PF. A similar approach used in Margulis et al. (2019) assimilated infrequent (i.e., a couple of observations per year) lidar snow depth observations within a land surface model. They demonstrated that data assimilation provides a useful framework for leveraging infrequent remotely sensed snow depth observations to derive continuous (spatially and temporally) accurate estimates of unobserved variables such as SWE and snowmelt, even at times when observations are unavailable.

4.4. Spatially Distributed Updates

Spatial distribution updates are essential in operational analyses of in situ snow depth measurements. Most of the snow data assimilation research in the literature, however, are one-dimensional approaches, where one satellite observation type (i.e., SWE, snow depth, or snow cover extent) is used to update co-located modeled snow estimates. That is, snow updates can only be performed at the locations where an observation is available. One-dimensional techniques disregard spatial correlation across observations and model errors. In a few exceptions, De Lannoy et al. (2010) and Cantet et al. (2019) tested the effect of introducing spatial error correlation into snow data assimilation updates. De Lannoy et al., (2010) assimilated coarse-scale (25 km) SWE observations into fine-scale (1 km) land model simulations and tested the effect of different spatial aggregation and correlation methods. Their results indicate that assimilating disaggregated fine-scale observations independently is less efficient than assimilating a collection of neighboring correlated coarser scale observations. Cantet et al. (2019) assimilated SWE data from a sparse network of in-situ snow observation stations using a PF. Their PF formulation included error spatial correlations to allow for snow states to be updated at locations where observations were not directly available. These few studies indicate that underlying spatial error correlations should be exploited to improve spatial estimates of seasonal snow.

4.5. Multi-Sensor Data Assimilation

Only a few studies have focused on multi-spectral, multi-resolution and multi-sensor data assimilation approaches. In fact, merging different observation types could be a challenging task (Girotto et al., 2019). A few exceptions include work by Durant and Margulis (2007), De Lannoy et al. (2012), Liu et al. (2013), and Zhao and Yang (2018). Durant and Margulis (2007) used EnKF in a multi-scale, multi-frequency radiometric data assimilation experiment using synthetic passive microwave radiance along with Vis/NIR snow cover extent observations. They stated that the combined assimilation of passive microwave and Vis/NIR observations resulted in overall improved snow predictive skill because of the positive synergy due to the complementary nature of the two observation types. Liu et al. (2013) assimilated MODIS snow cover extent and AMSR-E snow depth products into the Noah land surface model and concluded that the assimilation of snow data consistently improved snow and streamflow predictions. De Lannoy et al. (2012) assimilated AMSR-E SWE retrievals and MODIS snow cover extent observations. Their joint SWE and snow cover extent assimilation significantly improved root-mean-square error and correlation values. Zhao and Yang (2018) assimilated MODIS, GRACE and AMSR-E and found that the assimilation of MODIS snow cover fraction slightly improves snow estimation in mid and high latitudes while the assimilation of GRACE has potential in improving snow depth estimation in most high-latitude regions. The studies reviewed here agree that a broader range of assimilated observations is an essential for optimizing the information content provided to the models to produce the best possible estimates of seasonal snow.

4.6. Snow Data Assimilation in Operational Forecast Systems

Even if the research field in snow data assimilation has evolved significantly over the last decade, operational systems use methods that are much simpler than the state-of-the-art research (Helmert et al., 2018). For example, the GlobSnow product (Luojus, et al., 2013) provides global gridded information on snow extent and SWE across the Northern Hemisphere by incorporating in-situ station snow depth observations, microwave emission modeling, and spaceborne passive microwave observations using an iterative least squares minimization scheme. Another widely used product is SNODAS, developed by the National Oceanic and Atmospheric Administration (NOAA) (Barrett et al., 2003). SNODAS incorporates in-situ and airborne observations with model estimates to provide daily SWE at 1 km resolution across the continental US (Carroll et al., 2001). Its assimilation procedure is a simple nudging technique that calculates differences between estimated and observed SWE values and then spatially interpolates these differences to the model grid. Furthermore, the Canadian Meteorological Center Daily Snow Depth Analysis product (Brown and Brasnett, 2010) uses a simple statistical interpolation method to blend observations with model estimates of snow (Brown et al., 2003). Improved snow data assimilation schemes increase the skill of snow reanalysis products, which serve as an important baseline against which to assess climate model ensembles such as available in climate model intercomparison projects.

The work by Peings et al. (2011) and Lin et al. (2016) demonstrates that an accurate initialization of snow in a climate model has a positive impact on seasonal temperature forecast skill (**Figure 2**). Lin et al., (2016) showed that the assimilation of satellite measurements improves the initialization, with concomitant impacts on the forecast skill (Koster et al., 2017). Improvements at low latitudes are seen immediately and last up to 60 days, whereas improvements at high latitudes appear later in transitional (fall and spring) seasons (**Figure 2**). Finally, despite the importance of snow in regulating weather and climate processes, only a few global weather forecast centers include snow data assimilation schemes in their forecasting systems. One example is the European Center for Medium Weather Forecast (ECMWF) center which assimilates in-situ snow depth and satellite-derived snow cover extent (de Rosnay et al., 2014).

Zsoter et al. (2019) address an ongoing challenge in Earth System modeling and data assimilation applications. They show that while data assimilation of snow properties is a critical component of numerical weather prediction, the addition or removal of water neither conserves water mass nor does it reliably improve hydrologic prediction. The authors attribute the issue to getting the right answers for the wrong reasons; improvements in one model variable expose other model deficiencies. They call for a need to consider the whole Earth system in data assimilation and model coupling efforts. Such holistic Earth system approaches and the inclusion of diverse observations promise to provide robust information to improve our ability to map, model and project with a better degree of accuracy past, current and future seasonal snow characteristics and the effects of snow on the entire Earth System.

5. Conclusions

The international Earth Sciences community lacks an accurate way to estimate seasonal snow changes at sufficiently high temporal and spatial resolutions and with global coverage using any single in-situ, remote sensing or modeling technique. In this paper, we review current modeling, remote sensing and assimilation techniques used to estimate seasonal snow and elucidate the remaining challenges associated with each system.

The representation of snow in hydrologic and Earth System models has steadily improved over the last 60 years. To date, modeling efforts have provided the most spatially and temporally complete estimates of local, regional and global snow properties; however, the accuracy of snow model estimates remains hindered by uncertain forcing and parameters, and error-prone model structures and process representations.

Satellite and airborne remote sensing allow for extensive and global coverage of seasonal snow even in remote, complex mountainous regions. While snow cover extent and related surface properties are generally obtained reliably with high spatial and temporal resolution from visible and near infrared data, we critically lack similar robust estimates of snow mass relevant to water resource applications (Clifford 2010). Compared to Vis/NIR data, microwave measurements are more directly related to the mass of snow. While active microwave data have recently been found suitable for providing temporal and spatial resolutions for seasonal snow monitoring, passive microwave techniques are not useful for estimating deep or wet snow at an acceptable spatial resolution capable of resolving global snow processes inclusive of Earth's mountain water towers. Airborne lidar systems are, to date, the most accurate methods to retrieve seasonal snow, but they only observe snow depth (not SWE) and are limited to targeted regions and for specific, infrequent times.

Data assimilation is a viable way to converge different temporal and spatial resolutions of in-situ and remotely sensed observations and as a useful technology to bridge the scale gap between these observations and models. In fact, the assimilation of satellite and airborne observations lead, in general, to overall improved estimates of seasonal snow and related variables. Some remaining challenges in the snow data assimilation field include research in the effects of underlying spatial error correlations in data assimilation to improve the spatial estimates of SWE, and possibly merging multiple observations to improve snow model accuracy. Finally, even if the research field in snow data assimilation has evolved significantly, operational and weather forecasting systems use methods (if any) that are much simpler than the state of the art. The inclusion of a broader range of observations is an active and emergent research field as multi-sensor, multi-resolution snow observations become available.

These data assimilation efforts promise to provide robust and diverse information to improve our ability to map, model and project past, current and future characteristics and the effects of seasonal snow on the Earth System.

Figures and Tables

Table 1. Key Visible and Near Infrared (Vis/NIR) and passive microwave (PM) satellite missions that have been used for estimating seasonal snow.

Satellite or Sensor	Operational Period	Spectral Resolution	Spatial Resolution	Temporal Resolution	Spatial Coverage
Landsat	1972-present	Vis/NIR	15-120 m	~16 days	Global
MODIS	2000-present	Vis/NIR	250-1000 m	<Daily	Global
AVHRR	1978-present	Vis/NIR	1090 m	Daily	Global
VIIRS	2011-present	Vis/NIR	375 m	<Daily	Global
Sentinel-2	2018-present	Vis/NIR	20 m	~ 5 days	Regional
SMMR	1978-1987	PM	25 km	Every other day	Global
SSM/I	1987-present	PM	25 km	Daily	Global
AMSR/E	2002-2011	PM	25 km	Daily	Global
AMSR 2	2012-present	PM	25 km	Daily	Global

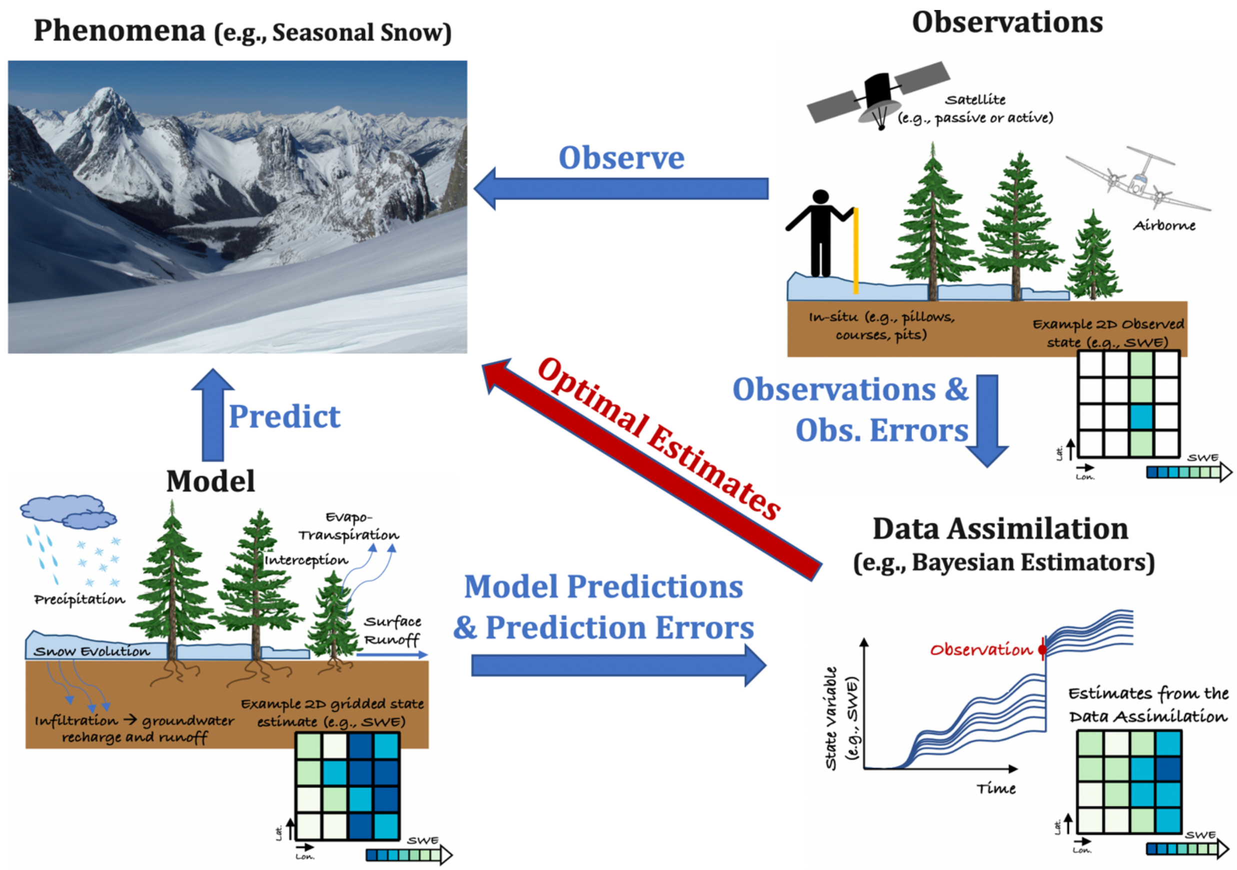

Figure 1. Estimates of an environmental variable (e.g., seasonal snow) can be obtained from model predictions or from observations (remote sensing or in-situ). Neither are perfect and they contain errors and uncertainties. Data assimilation can be seen as a method that combines the strengths of modeled and observed estimates to obtain an optimized set of estimates for the environmental variable.

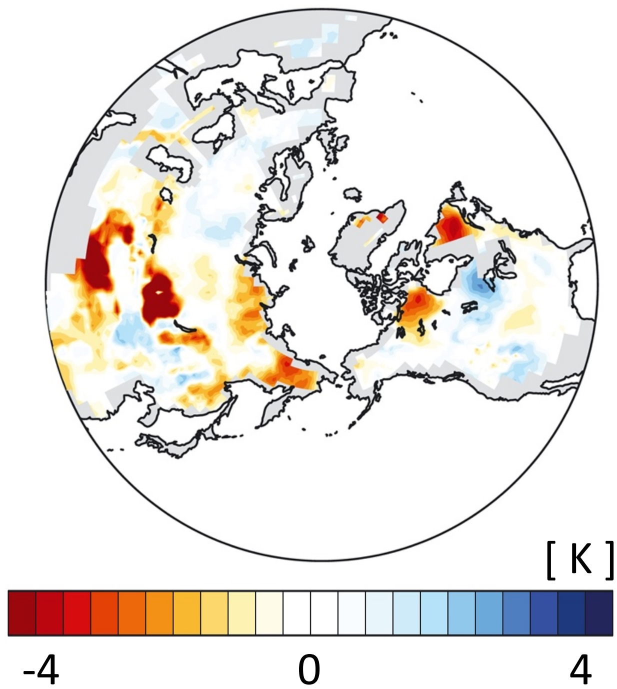

Figure 2. Improvements in temperature 3-month prediction due to assimilation of MODIS snow cover extent. Improvements are expressed in terms of cumulative RMSE difference between the model run that assimilated snow information and a run with no assimilation. Negative values indicate reduced prediction errors and improved temperature predictions after using snow data assimilation constrained land initializations. This is an edited version of Figure 2 in Lin et al., (2016).

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